DIGITAL TWIN AND AGENT-BASED SIMULATION: CO-SIMULATION TO SUPPORT INTELLIGENT NAVIGATION OF HEALTHCARE MOBILE ROBOT

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ABSTRACT

This article argues that important real-world characteristics needed to guide intelligent navigation of mobile robot in hospital units, are not currently being captured, and as a result, acceptance of mobile robots in hospital environments remains low. To enhance the scope and quality of the real-world information for mobile robot, a co-simulation framework is proposed, combining immersive digital twin (DTS) and agent-based simulation (ABS). This article conceptualized in-hospital mobility, developed a proof-of-concept system for the co-simulation, and demonstrated the co-simulation outcomes. This novel co-simulation framework is expected to help build a multifaceted world map as a foundational basis of intelligent navigation.

Keywords: digital twin, agent-based simulation, in-hospital mobility, mobile robot.

1 INTRODUCTION

Physical movements, interactions, and transportation methods employed within hospital units are integral to care delivery. Enhanced or constrained mobility therefore directly impacts allied health personnel performing and patients receiving care. In-hospital mobility can be improved through ergonomic environment design, which yield positive outcomes to productivity and safety (u 2016). For example, ergonomic arrangement of components (such as facility layout and medical devices) in terms of clinical importance and sequence-of-use (Sanders and McCormick 1987), can help care providers obtain a clear line-of-sight and access resources with minimal movements. Spared trips and movements accumulated over number of staffs and workhours directly improve productivity; a statistical prediction model for nurse work demand estimates that reducing the number of cumulative steps to walk during workhours lowers the level of fatigue measured at the end of the shift (Brzozowski et al. 2021). Besides, streamlined mobility may also help reduce patients' risks of trip and fall. However, (re)design of physical environment could be limited in its scope and consequences. The (re)design of hospital environments is often difficult in nature due to regulations with OSHA guidelines.

Alternatively, a more fundamental solution is to use mobile robots to take over some or all of the tasks on hospital units that involve highly repetitive or strenuous physical movements such as patient transfer, handling, and monitoring, or service activities associated with cleaning, maintenance, and logistics. For example, more than 850 man-hours are being spent on a weekly basis in a 500-bed hospital by nurses for transfer of goods, samples, and medical wastes.

These tasks do not add clinical value to patient outcomes (Ozkil et al. 2009). Despite a broad range of applications demonstrated over the past decade (Siegwart, Nourbakhsh, and Scaramuzza 2011), acceptance of mobile robots in hospital environments remains low (Ramdani et al. 2019); and more than 40% of innovative technologies including robots have failed or have been abandoned in the last two decades (Greenhalgh et al. 2017). The COVID-19 pandemic and the soaring needs to carry out disinfection, cleaning, and other increased logistic services, do not appear to have significantly improved the acceptance of mobile robots (Sierra Marín et al. 2021).

In fact, developing mobile robots to address mobility issues in hospital environments poses unique challenges not shared with other application domains. Mobile robots are generally expected to move without assistance from external human operators through its "intelligent" abilities to determine actions to complete a task (Siegwart, Nourbakhsh, and Scaramuzza 2011). Navigation is at the core of those intelligent abilities (Rubio, Valero, and Llopis-Albert 2019), fulfilling the functional tasks of generating a model of the environment (i.e., world map) by mapping sensor information, computing a collision-free trajectory, and moving along the trajectory. Optimal path planning (Raja and Pugazhenthi 2012) in a classic sense, which is to determine a collision-free path from a start to a goal point while minimizing travel distance (or in rare occasions, time, or energy), is only a basic ability needed for navigation in hospital settings. Yet the ability never guarantees acceptance by a heterogeneous group of care providers, staff, patients, and families. Imagine a mobile robot attempting to pass through a narrow hallway occupied by slow-walking mobility-aided patients and simultaneously an emergency team racing to transport a critical patient on a stretcher. Will people under such a situation accept the robot as a dependable companion as long as it keeps a moving along a collision-free path? For teamwork and collaboration with a mobile robot, what do care providers and staff expect of the robot mobility behaviors? Observing how people perceive and respond to mobility issues in hospital (Andersen et al. 2009; Fisher et al. 2011; Pavon et al. 2020), a truly intelligent solution would necessitate the robot to consider the entire systems of physical and cultural environment, administrative support structure, expectations of mobility roles, and teamwork for coordination and cooperation (Stutzbach et al. 2021).

A first step to tackle the complex navigation of healthcare mobile robot is to build and update an information-rich representation around mobility environment or world map, which contains key layers of systemic information about physical, institutional, and cultural environments, as well as dynamic information about stakeholders (i.e., people on the hospital floor, their roles, and tasks), teamwork, and safety issues. To that end, the current article proposes a co-simulation-in-the-loop approach that integrates digital twin (DTS) (Kim et al. 2022) and agent-based simulation (ABS) (Huang et al. 2018) for a mobile robot control in the loop, so this novel co-simulation framework serves to build a multifaceted world map as a foundational basis to formulate an intelligent navigation solution.

This article conceptualized, developed, and demonstrated initial outcomes of the proposed co-simulation. Section 2 provides ground works to identify healthcare-specific requirements for in-hospital mobility, and then overviews the trends of mobile robot navigation, so that building a comprehensive and context-rich world map is justified. Section 3 proposes key rationales for the development of DTS-ABS co-simulation. Section 4 details the methods of implementation for DTS and ABS, and then their integration for co-simulation. Section 5 discusses clinical implication of the co-simulation results and derives expected components needed for the world map, based on which mobile robots of the future can navigate in a truly acceptable manner.

The proposed co-simulation framework applied to the intelligent robot navigation planning in hospital units is new in terms of its concept (i.e., incorporating work-related knowledge in navigation planning), method (i.e., combining digital twin and agent-based simulation for predictive performance modeling), and application (i.e., seeking strategies to help robots be better accepted and streamlined into the healthcare workflows).

2 GROUND WORKS

2.1 Evolution of Mobile Robot Navigation

A mobile robot's planning for in-hospital navigation is well beyond an optimization problem that uses a computationally efficient algorithm to generate valid navigation paths not interfering with obstacles (Raja and Pugazhenthi 2012). Collision avoidance is just one of many requirements typically imposed on mobile robot applications. To reliably carry out navigation, mobile robot is expected to demonstrate the following intelligent abilities (Rubio, Valero, and Llopis-Albert 2019):

- Perception: The robot can use its sensors to acquire information about the environment.
- Localization and mapping: The robot maintains the information of its position and configuration within the environment.
- Cognition: The robot can decide on its best course of action for navigation path, trajectory, and motion.
- Motion control: The robot can specify its forces on the actuators to achieve intended navigation outcomes.

Similar to the cases in human intelligence such as perceptual judgment, proprioception, and motion imagery (Gazzaniga, Ivry, and Mangun 2002), those four abilities are not clearly distinct with one another; strengthening or impairing one ability (e.g., perception) could enhance the others (e.g., localization and mapping). It is because of the common component that weaves through all underlying abilities in robot navigation, which is information about the "world", including the navigation environment, objects, people, and the robot itself.

Accuracy of the world information is crucial for localization (not only tracking the robot's absolute position in the environment, but also its relative position with respect to other people and objects), map representation, cognition, and motion control. Thus far, a wide array of sensors, systems, and methods have been developed to enhance the accuracy for mobile robot (Borenstein et al. 1997; Rubio, Valero, and Llopis-Albert 2019). Still, despite ongoing research activities, important real-world characteristics are not well represented in the world information for mobile robots, which substantially limits their acceptance and perceived trust among people who work around them. A potential pitfall of amplifying data to enhance the world information is computational complexity that ripples through map representation, cognition, and motion control (Rubio, Valero, and Llopis-Albert 2019). The pursuit of higher resolution and multimodality in sensing could be limited in this regard. Besides, sensor-oriented geometric and kinematic data is only a fraction of the world information that humans process to perform their real-world tasks. Taking a driving task, for example, human drivers easily consider multiple layers of real-world information such as traffic rules and pedestrian behaviors, well beyond the longitudinal and lateral control of the car.

The key rationale of this article is thus, to enhance the scope and quality of the world information, through the proposed co-simulation approach, up to high-level information about work system and society, so the robot navigation in hospital environment under diverse realistic scenarios will comply with workflows, organizational protocols, and even ethical rules. It is a viable solution to fulfill the requirements of diverse stakeholders and complicated work system protocols, so mobile robot can be better accepted.

2.2 Key Characteristics and Axioms for In-Hospital Mobility

The recent extensive review calls for systemic approaches to contrive solutions for in-hospital mobility (Stutzbach et al. 2021). This systems-oriented view can broaden the scope of the world associated with mobility, and also helps identify key information elements needed to be represented in the world map. Suppose that redundant commands are routinely issued (and then cancelled) by multiple clinicians for a mobile robot to navigate back-and-from a stock room. An intelligent navigator may want to seek more information around those navigation calls, learn that the lack of communication among clinicians is the main cause of redundant calls, and as results, inform all related clinicians of an incoming navigation call before it starts to move. In this fictitious scenario, the world information needed for intelligent navigation is the list of recent calls, related clinicians and their work activities, which help understand the motivation and risks behind each navigation call.

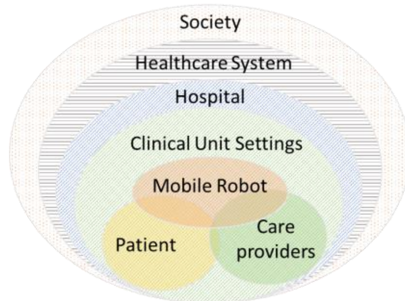

Figure 1: The healthcare systems hierarchy associated with in-hospital mobility.

Based on the in-hospital mobility literature (Lucas and Benson 2019; Kortebein 2009; Pavon et al. 2020; Fisher et al. 2013, 2011; Koenders et al. 2020; Stutzbach et al. 2021), the following axioms are derived to characterize in-hospital mobility. Although the literature primarily focused on patient mobility, the axioms were generalized to include mobility of all stakeholders in hospital, including clinicians, nurses, staffs, patients, and families, regardless of mobile robot use:

1. Mobility Expectation axiom: A call to navigate between two disjoint points on hospital floor is initiated by the set of hierarchical expectations from among individual stakeholders, clinical unit, hospital management, healthcare system, and society; see the healthcare systems hierarchy in Figure 1. A completed navigation call may align with, indifferent, or contradict each one of the expectations in the hierarchy.
2. Mobility Execution axiom: The specific manner to execute a navigation call such as role (i.e., who is responsible for this navigation call) and priority, are determined by physical environment, workflow, infrastructure, resources, and culture, and those multi-factors span the healthcare systems hierarchy.
3. Mobility Coordination axiom: A team approach to communicate, coordinate, and cooperate on a navigation call produces better outcomes in terms of mobility performance and addressing contradictory expectations.

The three axioms defined will be further elaborated in the co-simulation approach proposed in the next section. Our co-simulation is expected to provide mobility-related, context-rich information about the world (e.g., mobility stakeholders' expectations, physical environment, workflow, resources, and culture), as to build the world map representation as the future basis of intelligent navigation behaviors.

3 PROPOSED APPROACH: CO-SIMULATION FOR WORLD MAP REPRESENTATION

3.1 Digital Twin Simulation (DTS) of Human-Robot Interaction (HRI) in Hospital

Digital twin originally refers to a broad set of "virtual information constructs that fully describes a physical manufactured product" in the context of product life-cycle management, so that valuable information about the physical product can be obtained cost-effectively from its digital replica (Grieves 2014). Following literature on DTS has focused on creating and maintaining a highly accurate representation of the physical counterpart through bidirectional information exchange between the physical and digital twin (Khan et al. 2018).

Contrary to predominantly physical products in manufacturing domain, healthcare DTS requires to expand the scope of simulation that includes people of different roles, data, equipment, and personnel training outcomes. Motivated by the vision to represent a full breadth of human-robot interaction (HRI) in intensive care unit (ICU), the authors' prior work developed a proof-of-concept DTS in virtual reality (VR) by integrating robot operating system (ROS) with the Unity3D VR platform (Kim et al. 2022). Currently, the DTS continues to expand in its scope by incorporating other simulation components related to HRI at ICU, including a simulated electronic medical record (EMR).

3.1.1. Navigation of a Mobile Robot

This article used a two-wheeled mobile robot provided by the OhmniLabs Inc. For navigation, the robot uses a built-in 2D LiDAR sensor for localization. The robot control system uses two built-in communication channels to first receive a navigation command from a remote operator via a web application (NativeJS), and then to translate it to the corresponding low-level servo and motor-control (ROS docker image). A default navigation scenario is manual operation; a human operator remotely decides on the paths and configures its movement. For advanced navigation scenarios, the article used the OhmniLab's specialized TB Control ROS node to communicate with the DTS running in Unity3D. This connection of the physical robot with DTS permits flexibility in control sources, so that either a physical (i.e., human operator) or virtual entity may take over navigation. Further pushing the boundaries of the virtual entity leads to artificial intelligence (AI) for autonomous navigation.

3.1.2. Immersive Digital Twin Simulation (DTS)

The immersive DTS, or Extensive Simulation (Kim et al. 2022), aims to create a highly realistic digital replication of human-robot interaction (HRI) that simulates, not only physical appearance and dynamic navigation of mobile robot, but also human behaviors arising from interacting with the robot. The concept of immersion broadly refers to an "objective description of reality delivered by technology" that appeals to the sense of human with an "inclusive, extensive, surrounding, and vivid illusion" (Slater 2009). Healthcare domain has long adopted immersive simulation, predominantly for the training and evaluation of clinical skills, problem solving, and judgment (Rosen 2008).

This proposed integration of digital twin with immersive simulation may potentially overcome the fundamental limitation of current DTS in configuring human-robot collaboration (Kousi et al. 2021), which was to disproportionately concentrate on robot configuration only while neglecting human's adaptability (Miller et al. 2005), perhaps due to the lack of statistically-reliable information about humans at work. Immersive DTS can facilitate knowledge discovery of emergent human behaviors by placing user(s) in a highly contextualized situation. It also helps collect a large set of activity instances on a given virtual ICU environment and scenarios to help generalize on human actions, and further derive statistically-valid human models.

3.2 Agent-Based Simulation (ABS) to Gain Insights on HRI

Agent-based simulation is a variation of discrete-event simulation, aimed at describing the behavior and interaction of "agents", or autonomous entities, which can perceive its environment, make decisions, and adapt behaviors over time (Law, Kelton, and Kelton 2007). Human-robot interaction (HRI) in hospital settings is particularly suited for analysis using the ABS; according to the Mobility Execution and Coordination axioms in Section 2.2, people or mobile robot on the hospital floor is likely to interact with one another and adapt their own mobility behaviors based on perception of the environment and the other agents, rather than moving as preprogrammed.

There are many simulation platforms to implement the ABS, including Simio, AnyLogic, Aveva, and FlexSim. This article chose FlexSim for its advantages of healthcare focused simulation features and the ability to simulate flexible trajectories. FlexSim is particularly useful in finding an optimal navigation path because of its built-in A* algorithm (this algorithm works using weighted graphs; starting from an initial node from a graph, it builds a tree of paths starting from that node, explores the possible paths one step at a time until one of its paths ends at the targeted node (Rubio et al. 2009).

3.3 Co-Simulation of DTS and ABS

The immersive DTS reproduces a digital-twin robot (a real-time digital representation of physical robot including its appearance and navigation), user group interactions (collected through VR headset and wearable sensors), and the hospital environment (designed in VR to represent an actual care environment).

DT and ABS co-simulation have been used to monitor healthcare departments' current state in real time, current and future states according to predictive simulation, and future states (Moyaux et. Al, 2023). This article showcases an example use case studying patient flow in the emergency department. The DT shows the current state of the physical twin (PT) while ABS allowed users to run various replications and what-if scenarios (Barat et. al, 2019)

3.4 Co-Simulation-In-The-Loop for Navigation Control

As envisioned in Section 1, the co-simulation outcomes will enhance the scope and quality of the world information needed for intelligent navigation. An advanced mobile robot will, thus, navigate with this co-simulation in-the-loop. Such hybrid system framework is at a very early stage (Huang et al. 2018), and has potential for cost-effective systems synthesis.

4 CO-SIMULATION IMPLEMENTATION

This section presents details of system architecture and implementation methods and illustrates key simulation results.

4.1 Immersive Digital Twin Simulation (DTS) Architecture

The Unity3D engine provided the main platform for developing the digital-twin environment. Its integration with the ROS through the TCP Connector and Endpoint packages enabled implementation of the immersive DTS. Particularly, the ROS integration allowed for the bidirectional connection for data flow and control commands; see Figure 2.

For the reference of physical environment, the Jump Simulation Center located at the University of Illinois Urbana-Champaign campus was accessed by the authors. It is a high-fidelity simulation facility designed

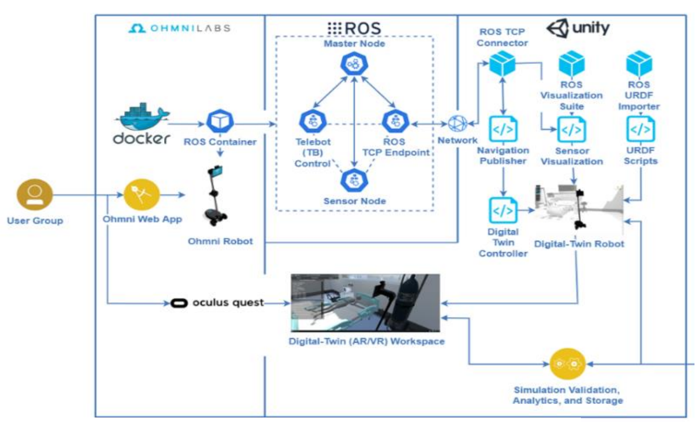

Figure 2: Digital Twin Simulation Architecture for a Mobile Robot.

Figure 3: Illustration of immersive digital-twin simulation.

for experiential medical education. Particularly, access to the ICU, patient rooms, nursing station, and hallway allowed the authors to fully replicate the hospital environment including ventilator, bed, patient monitor, and simulated patient; see the top panel in Figure 3. It also allowed for serial testing without interference of bed placement, disrupt discharge, or admission processes that would otherwise be timely and costly in actual hospital settings. Comparative testing of the robot navigation in physical versus digital environment (the middle and bottom panels in Figure 3) shows minimal discrepancies; average time delays during a 5-minute simulation session were only less than 10 milliseconds. In Figure 3, the hospital layout is digitally replicated for VR (top left); a nurse's catheterization task supported by the robot's catheter kit delivery (top right); physical versus digital twin for robot navigation on the hallway (middle), and robot positioning for patient monitoring (bottom).

4.2 Agent-Based Simulation (ABS) Implementation

FlexSim was used for the implementation of the ABS. The platform requires specifying the dimensions of the hospital environment including wall thickness. The dimensions were estimated from the layout in the top left of Figure 3. Since decimals are not accepted for the dimension input in the FlexSim, the simulation dimension was upscaled by a factor of 10. There are 4 patient rooms and a storage room, which were utilized to simulate the real-world DT application with the ABS. The real-world DT application utilized 3 patients with scheduled activities and healthcare professionals, which allowed for a baseline in the simulation atmosphere. The patients' names are Martha, Sonia, and John. Martha has been in the center after an injury while Sonia and John are newly admitted patients, as can be seen in Table 1. That does not include all patient events and shows a sample of the patient timeframes.

Table 1: Patient scenarios.

11 pm	11:02	11:04	11:06	11:08	11:10	11:12	11:14	11:16
Sonia admitted to unit	Initial history and assessment				Oxygen 85%, alarms ringing	Ask robot to call nurse	Asks robot to call physician for orders	Ask robot to call physician for vaso-pressor

Figure 4 shows the patient scenarios from Table 1 built out. Laymen terms are utilized to provide easier readability in the patient process flows. The simulations process flow shows staff moving throughout the center. For instance, in Figure 4, the robot/cobot is obtaining towelettes that will then be later used to clean the patient with the health care tech (HCT). A process flow was created for each patient to show their care in the HCES.

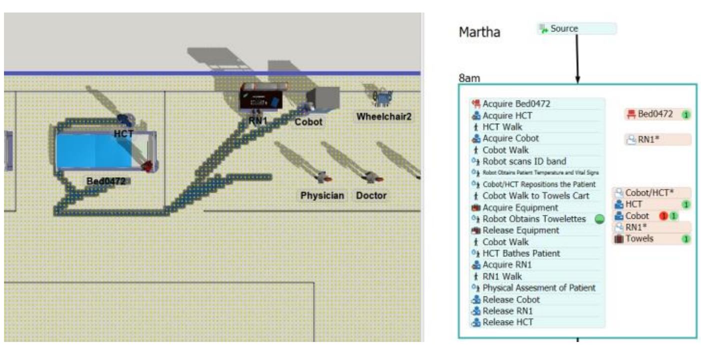

Figure 4: FlexSim patient scenarios.

Currently, only 1 registered nurse (RN) is available, so when the other patients are admitted to the unit pre-emption will be utilized to give priority to certain patients. Pre-emption will be useful when a patient with severe health conditions requires attention.

Table 2: Agent based simulation (ABS) input elements.

Simulation component	Related subcomponents/ properties/ variables
Source	- Front Door - Arrival Style: IAT, Arrival Schedule, Arrival Sequence; distribution; table lookup
Queue	- Front Desk - Queue max content limits the number of patients checking in or in the waiting area - Output: use transport of nurse
Room (Inpatient/ Outpatient/ ICU)	- Processor: a) Max content: the number of patients in room (1). b) Setup time. c) Process Time: i) Distribution. ii) Table Lookup. iii) Use operators (robot and nurse) to perform tasks. - Output: a) Utilized to allow patients to leave room. b) Used transport of nurse.
Sink	Leave center
Monte Carlo	- Multiply the sample from the DT - Replications

Table 2 defines simulation components, associated subcomponents and properties, used to implement the ABS for the hospital units. The simulation outcomes include work-in-progress (WIP), travel distance for robot and human agents, and throughput in the system.

4.3 ABS Outputs

The outputs of the ABS provide accurate results as the durations of patient activities are timed, dimensioning of the HCES is implemented and equipment are to scale. With the use of experimentation, studies can be evaluated such as the number of staff available, staff priorities, and time to complete tasks. With the use of the DT and ability to experiment with mannequins, scenarios and experiments can be studied further.

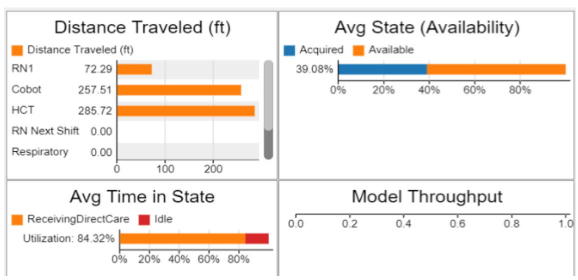

Figure 5: Output results of simulation.

Figure 5 shows a dashboard of values to be tracked instantaneously. In this figure, the distance traveled of staff members are tracked. The average state of each staff member is also recorded to see when they are acquired by another patient or available. The availability of staff will be useful for staff allocation. The patients' average time in state is also recorded as receiving direct care or being idle. Lastly the model throughput tracks patients leaving the center. With experimentation this simulation can be run various times to see the average throughput of patients and their utilization.

4.4 ABS Results

Although the build of the simulation is not yet complete, results can be taken from FlexSim reports and dashboards like Figure 5 to compare to the DT real-world application. These results can show the optimal travel paths of staff, utilization of resources (staff, storage rooms, etc.), patient care utilization and much more.

4.5 DTS-ABS Integration

The DTS-ABS integration implements co-simulation and analytics services within the simulation platform; the combined simulation approach is proposed between the ABS implemented in the FlexSim and the digital twin platform created within the Unity. The coordination between Unity and FlexSim is achieved via an SQL Database and a Webserver with general system architecture as follows: The connection between Unity and a robot with a standard Robot Operating System (ROS) distribution was demonstrated (Kim et al. 2022). From Unity, web requests are made to a webserver that communicates with the shared SQL database. Data from Unity can then be shared with FlexSim as input to various agent-based simulations. The results from such simulations are then sent back to Unity for further decision making within the digital twin.

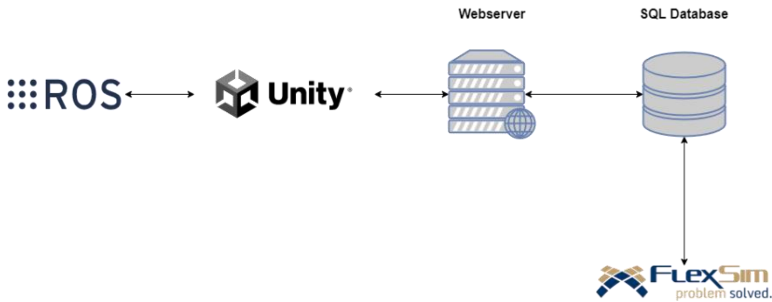

Figure 6: System architecture to combine immersive digital-twin and agent-based simulation.

The ABS provides an interface to input the high-level organizational policies of the hospital into a simulation which can then inform lower-level control models. For instance, various robotic kinematic models can be tested within the ABS to minimize distance traveled of human agents, decrease patient waiting time, and maintaining safe nurse utilization and patient-to-nurse ratios as per the safety guidelines and policies of the hospital organization. As a result, changes to the current robotic kinematic model can gradually be deployed and validated within the DTS. Real-time updates facilitated by the DT can then inform further optimizations to the kinematic model along with capturing new input data for the ABS such as updates to the world map. These updates will help guide the robot in navigating the physical environment when choosing the optimal path.

5 DISCUSSION: ESTABLISHING WORLD MAP

5.1 Clinical Implication for the World Map

The co-simulation framework is expected to generate various metrics related to agent activities on hospital units, shedding light on productivity. The below are examples of the metrics:

- Average number of nurses available
- Average time in hospital units spent on different tasks or units
- Average waiting time for clinicians/ to see a nurse
- Average travel speed of robot

Utilizing the aforementioned metrics to navigate the robot, the robot's autonomous movement replicates the movement of a nurse or an allied health care professional that is participating in patient care. Replication of navigation during patient care and in patient care units will provide insight into active travel distance, time required in travel, stationary time spent doing direct patient care or charting, time spent in stationary time, and idle time where no activities are occurring. This granular description will provide objective measurement to depict patient acuity and level of care required, and efficacy of physical layout and traffic flow of patient care units. This information will improve utilization of human resources through complementary patient care assignments to maximize nursing skills and time and increase patient safety and reduce resource fatigue, as well as design of patient care units to maximize use of human resources.

6 CONCLUSION

The current work proposed a co-simulation approach combining immersive digital twin (DTS) (Kim et al. 2022) and agent-based simulation (ABS) to support intelligent navigation of mobile robots in hospital units. This article conceptualized, developed, and demonstrated initial outcomes of the proposed co-simulation. This co-simulation framework is expected to help build a multifaceted world map as a foundational basis to formulate an intelligent navigation solution. For a scalable solution, more robust simulation architectures are needed be explored to mitigate latency, increase reliability, and harden security (Zeb et al. 2022; Lu et al. 2021; Mashaly 2021; Huynh et al. 2022). The implementation of real-time agent-based simulation with a digital twin requires to addressing it. Additionally, optimizations would need to occur based on medical situational awareness as certain types of data would have higher priority than others when it comes to the dimensions of latency, reliability, and security. While solutions have been proposed within manufacturing, healthcare digital twin solutions will require further exploration, testing, and common metrics for comparing different digital twin solutions, each having their own advantages, disadvantages, and features. This will be explored in future research. In future research, the ABS will be utilized to run experiments by changing the parameters for the number of staff available, patients receiving care, and the robot assistance level. This information can be useful to see how parameters affect the travel path of staff members and patients. Lastly, by adding longer sessions for the evaluation of the simulation, the number of errors will be reduced by ensuring the simulation is as close to the real world as possible.

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REFERENCES

Alvarado, C. J. 2016. “The Physical Environment in Health Care.” In *Handbook of Human Factors and Ergonomics in Health Care and Patient Safety*, 244–63. CRC Press.

Andersen, P., A-M. Lindgaard, M. Prgomet, N. Creswick, and J. I. Westbrook. 2009. “Mobile and Fixed Computer Use by Doctors and Nurses on Hospital Wards: Multi-Method Study on the Relationships between Clinician Role, Clinical Task, and Device Choice.” *Journal of Medical Internet Research* 11 (3): e32.

Barat, S., V. Kulkarni, T. Clark, and B. Barn, "An Actor Based Simulation Driven Digital Twin For Analyzing Complex Business Systems," *2019 Winter Simulation Conference (WSC)*, National Harbor, MD, USA, 2019, pp. 157-168.

Borenstein, J., H. R. Everett, L. F., and D. Wehe. 1997. “Mobile Robot Positioning: Sensors and Techniques.” *Journal of Robotic Systems* 14 (4): 231–49.

Brzozowski, S. L., H. Cho, É. N. A. Knudsen, and L. M. Steege. 2021. “Predicting Nurse Fatigue from Measures of Work Demands.” *Applied Ergonomics* 92: 103337.

Fisher, S. R., J. S. Goodwin, E. J. Protas, Y-F. Kuo, J. E. Graham, K. J. Ottenbacher, and G. V. Ostir. 2011. “Ambulatory Activity of Older Adults Hospitalized with Acute Medical Illness.” *Journal of the American Geriatrics Society* 59 (1): 91–95.

Fisher, S. R., Y-F. Kuo, G. Sharma, M. A. Raji, A. Kumar, J. S. Goodwin, G. V. Ostir, and K. J. Ottenbacher. 2013. "Mobility after Hospital Discharge as a Marker for 30-Day Readmission." *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences* 68 (7): 805–10.

Gazzaniga, M. S., R. B. Ivry, and G. R. Mangun. 2002. "Cognitive Neuroscience, New York: W. W." Norton & Company.

Greenhalgh, T., J. Wherton, C. Papoutsi, J. Lynch, G. Hughes, S. Hinder, N. Fahy, R. Procter, and S. Shaw. 2017. "Beyond Adoption: A New Framework for Theorizing and Evaluating Nonadoption, Abandonment, and Challenges to the Scale-up, Spread, and Sustainability of Health and Care Technologies." *Journal of Medical Internet Research* 19 (11): e8775.

Grieves, M. 2014. "Digital Twin: Manufacturing Excellence through Virtual Factory Replication." *White Paper* 1: 1–7.

Huang, S., W. Wang, M. R. Brambley, S. Goyal, and W. Zuo. 2018. "An Agent-Based Hardware-in-the-Loop Simulation Framework for Building Controls." *Energy and Buildings* 181: 26–37.

Huynh, D., V-D. Nguyen, V. Sharma, O. A. Dobre, and T. Q. Duong. 2022. "Digital Twin Empowered Ultra-Reliable and Low-Latency Communications-Based Edge Networks in Industrial IoT Environment." In *ICC 2022 - IEEE International Conference on Communications*, 5651–56.

Khan, A., M. Dahl, P. Falkman, and M. Fabian. 2018. "Digital Twin for Legacy Systems: Simulation Model Testing and Validation." In *2018 IEEE 14th International Conference on Automation Science and Engineering (CASE)*, 421–26. Institute of Electrical and Electronics Engineers, Inc.

Kim, I., A. Nepomuceno, S. Jamison, J. Michel, and T. Kesavadas. 2022. "Extensive Simulation Of Human-Robot Interaction For Critical Care Telemedicine." In *2022 Annual Modeling and Simulation Conference (ANNSIM)*, 329–40. Institute of Electrical and Electronics Engineers, Inc.

Koenders, N., R. Oorsouw, J. P. H. Seeger, I. Glind, and T. J. Hoogeboom. 2020. "'I'm Not Going to Walk, Just for the Sake of Walking…': A Qualitative, Phenomenological Study on Physical Activity during Hospital Stay." *Disability and Rehabilitation* 42 (1): 78–85.

Kortebein, P. 2009. "Rehabilitation for Hospital-Associated Deconditioning." *American Journal of Physical Medicine & Rehabilitation* 88 (1): 66–77.

Kousi, N., C. Gkournelos, S. Aivaliotis, K. Lotsaris, A. C. Bavelos, P. Baris, G. Michalos, and S. Makris. 2021. "Digital Twin for Designing and Reconfiguring Human–Robot Collaborative Assembly Lines." *Applied Sciences* 11 (10): 4620.

Law, A. M., W. D. Kelton, and W. D. Kelton. 2007. *Simulation Modeling and Analysis*. Vol. 3. Mcgraw-hill New York.

Lu, Y., X. Huang, K. Zhang, S. Maharjan, and Y. Zhang. 2021. "Low-Latency Federated Learning and Blockchain for Edge Association in Digital Twin Empowered 6G Networks." *IEEE Transactions on Industrial Informatics* 17 (7): 5098–5107.

Lucas, J W, and V. Benson. 2019. "Tables of Summary Health Statistics for the US Population: 2018 National Health Interview Survey." *National Center for Health Statistics*.

Mashaly, M. 2021. "Connecting the Twins: A Review on Digital Twin Technology & Its Networking Requirements." *Procedia Computer Science* 184: 299–305.

Miller, C. A., H. Funk, R. Goldman, J. Meisner, and P. Wu. 2005. "Implications of Adaptive vs. Adaptable UIs on Decision Making: Why 'Automated Adaptiveness' Is Not Always the Right Answer." In *Proceedings of the 1st International Conference on Augmented Cognition*, 22–27.

Moyaux, T., Y. Liu, G. Bouleux, and V. Cheutet. 2023. "An Agent-Based

Architecture of the Digital Twin for an Emergency Department" *Sustainability* 15, no. 4: 3412.

Ozkil, A. G., Z. Fan, S. Dawids, H. Aanes, J. K. Kristensen, and K. H. Christensen. 2009. "Service Robots for Hospitals: A Case Study of Transportation Tasks in a Hospital." In *2009 IEEE International Conference on Automation and Logistics*, 289–94. Institute of Electrical and Electronics Engineers, Inc.

Pavon, J. M., R. J. Sloane, C. F. Pieper, C. S. Colón-Emeric, H. J. Cohen, D. Gallagher, K. S. Hall, M. C. Morey, M. McCarty, and S. N. Hastings. 2020. "Accelerometer-measured Hospital Physical Activity and Hospital-acquired Disability in Older Adults." *Journal of the American Geriatrics Society* 68 (2): 261–65.

Raja, P., and S. Pugazhenthi. 2012. "Optimal Path Planning of Mobile Robots: A Review." *International Journal of Physical Sciences* 7 (9): 1314–20.

Ramdani, N., A. Panayides, M. Karamousadakis, M. Mellado, R. Lopez, C. Christophorou, M. Rebiai, M. Blouin, E. Vellidou, and D. Koutsouris. 2019. "A Safe, Efficient and Integrated Indoor Robotic Fleet for Logistic Applications in Healthcare and Commercial Spaces: The ENDORSE Concept." In *2019 20th IEEE International Conference on Mobile Data Management (MDM)*, 425–30.

Rosen, K. R. 2008. "The History of Medical Simulation." *Journal of Critical Care* 23 (2): 157–66.

Rubio, F., F. Valero, and C. Llopis-Albert. 2019. "A Review of Mobile Robots: Concepts, Methods, Theoretical Framework, and Applications." *International Journal of Advanced Robotic Systems* 16 (2): 1-7.

Rubio, F., F. Valero, J. Sunyer, and V. Mata. 2009. "Direct Step-by-step Method for Industrial Robot Path Planning." *Industrial Robot: An International Journal* 36 (6): 594–607.

Sanders, M. S., and E. J. McCormick. 1987. *Human Factors in Engineering and Design*. McGRAW-HILL book company.

Siegwart, R., I. R. Nourbakhsh, and D. Scaramuzza. 2011. *Introduction to Autonomous Mobile Robots*. MIT press.

Sierra Marín, S. D., D. Gomez-Vargas, N. Céspedes, M. Múnera, F. Roberti, P. Barria, S. Ramamoorthy, M. Becker, R. Carelli, and C. A. Cifuentes. 2021. "Expectations and Perceptions of Healthcare Professionals for Robot Deployment in Hospital Environments during the COVID-19 Pandemic." *Frontiers in Robotics and AI* 8: 612746.

Slater, M. 2009. "Place Illusion and Plausibility Can Lead to Realistic Behaviour in Immersive Virtual Environments." *Philosophical Transactions of the Royal Society B: Biological Sciences* 364 (1535): 3549–57.

Stutzbach, J., J. Jones, A. Taber, J. Recicar, R. E. Burke, and J. Stevens-Lapsley. 2021. "Systems Approach Is Needed for In-Hospital Mobility: A Qualitative Metasynthesis of Patient and Clinician Perspectives." *Archives of Physical Medicine and Rehabilitation* 102 (5): 984–98.

Zeb, S., A. Mahmood, S. A. Hassan, M. D. J. Piran, M. Gidlund, and M. Guizani. 2022. "Industrial Digital Twins at the Nexus of NextG Wireless Networks and Computational Intelligence: A Survey." *Journal of Network and Computer Applications* 200: 103309.

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